ACO & GA @TSP

EDAA 23/24

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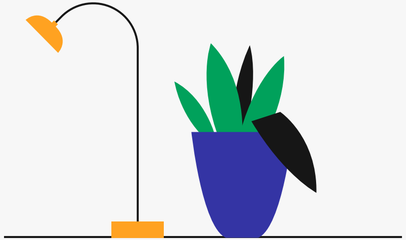
Content



01

The Problem

Traveling Salesman Problem (TSP)

Shortest Path

Given a graph, what's the shortest possible path visiting each city exactly once and returning to the origin.

NP-Hard

If there's a solution to the problem, it can't be found in polynomial time.

Naive Approach...

- For a simple instance with 10 cities, we would have to calculate 3,628,800 possible permutations.

- To address this challenge, various heuristic and approximation algorithms have been developed to find near-optimal solutions for the TSP without exhaustively searching through all possible permutations.

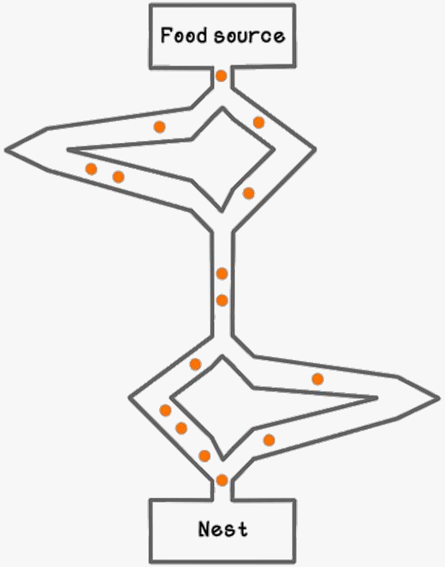
- These algorithms aim to efficiently explore the solution space and find good solutions without the need to consider every possible permutation.

02

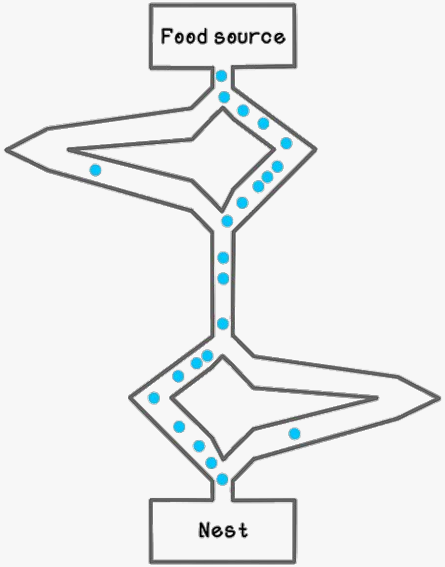
Ant Colony Optimization Approach

Finding the best route... Pheromones

Taking in note:
- Ants are blind;
- Each ant moves at random;
- Pheromone is deposited on path;
- More pheromone on path increases probability of being followed.



After 4 minutes



After 8 minutes

Pseudo-Code

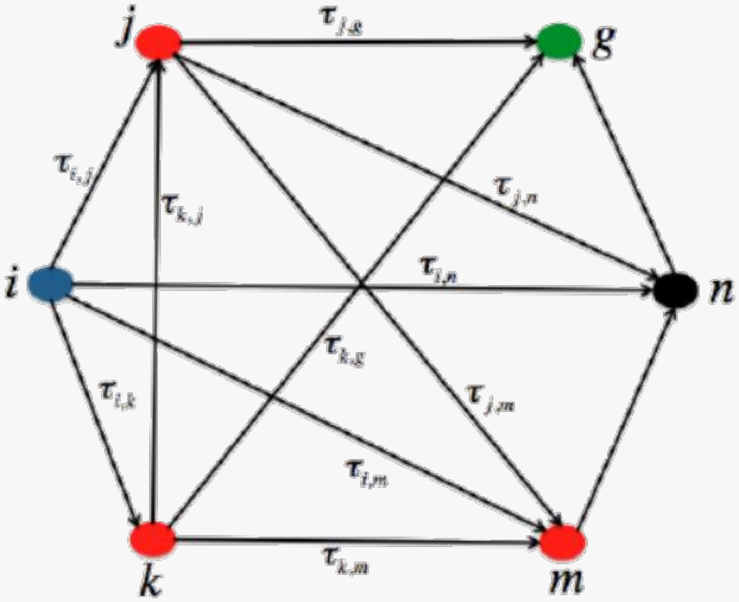
```
Begin ACO
  Generate Random Population
  While NOT stop DO:

    BEGIN
        Position Each Ant In Starting node
        Repeat
          For each Ant DO:
            Choose Next Node By Applying State Transition Rule
            Apply Step by Step Pheronome Update
          END For
         UNTIL every Ant has built a solution
         Update Best Solution
         Apply Offline pheronome update

     END
    Output the best solution
END
```

Path construction

How to select next node?

$$p_{ij} = \frac{[\tau_{ij}]^{\alpha}[\eta_{ij}]^{\beta}}{\sum_{h \in s}[\tau_{ij}]^{\alpha}[\eta_{ij}]^{\beta}}$$

i - origin
j - destination
τ - pheromone
η - inverse of distance
α - weight (parameter)
β - weight (parameter)



Pheromones Update

Local Update

$$\tau_{ij}(t) = (1-\rho).\tau_{ij}(t-1) + \rho.\tau_0$$

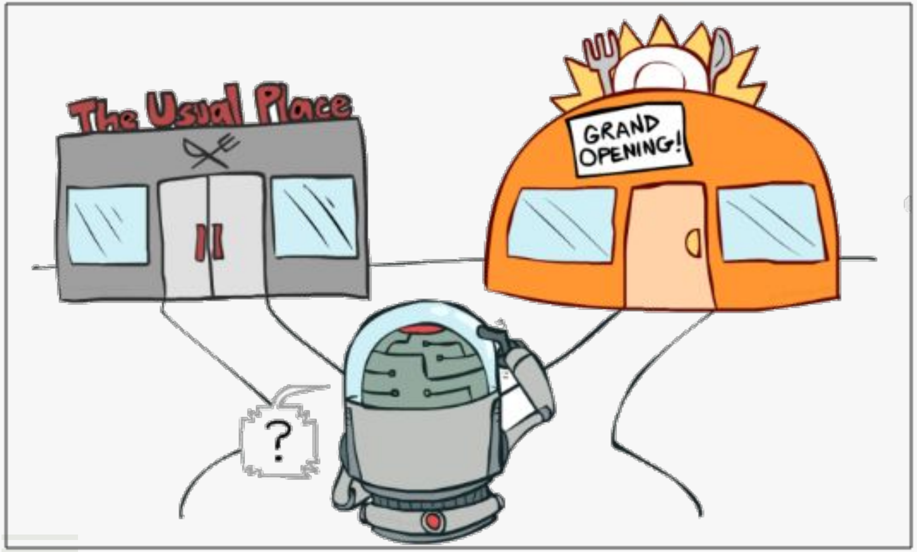
Global Update

$$\tau_{ij}(t) = (1-\rho).\tau_{ij}(t-1) + \frac{\rho}{L^+}$$

i - origin
j - destination
τ - pheromone
ρ - evaporation constant
t - time/length of path
L+ - length of best path generated

Exploration vs Exploitation

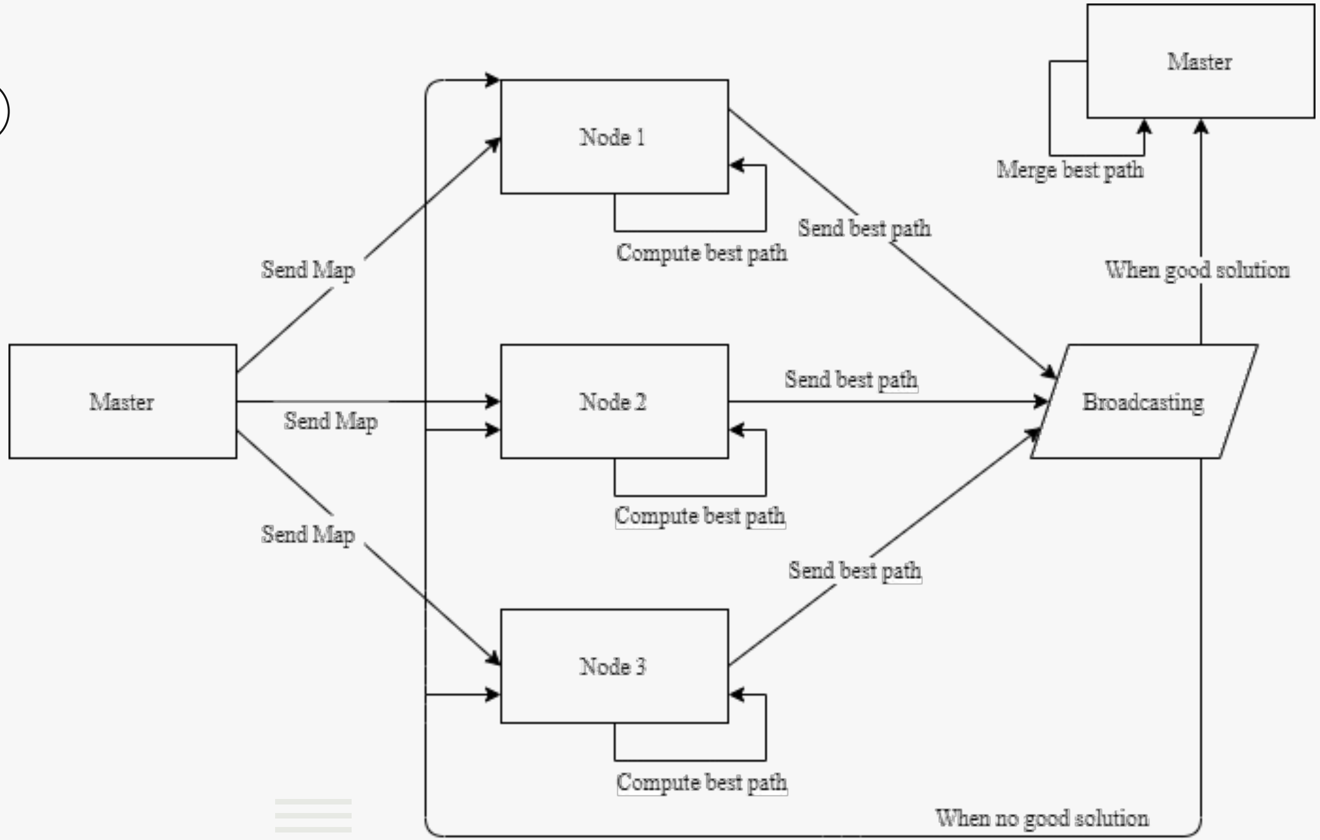
$$[\tau_{ij}]^{\alpha}[\eta_{ij}]^{\beta}$$

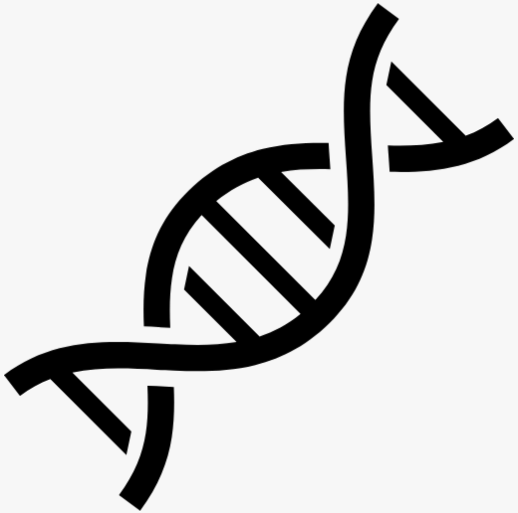


- α> exploration
ant move is random

- β> exploitation
benefit shorter edges

ACO Parallel





03

Genetic Algo. Approach

Terminology

Gene

It's basically a unit/element of a chromosome

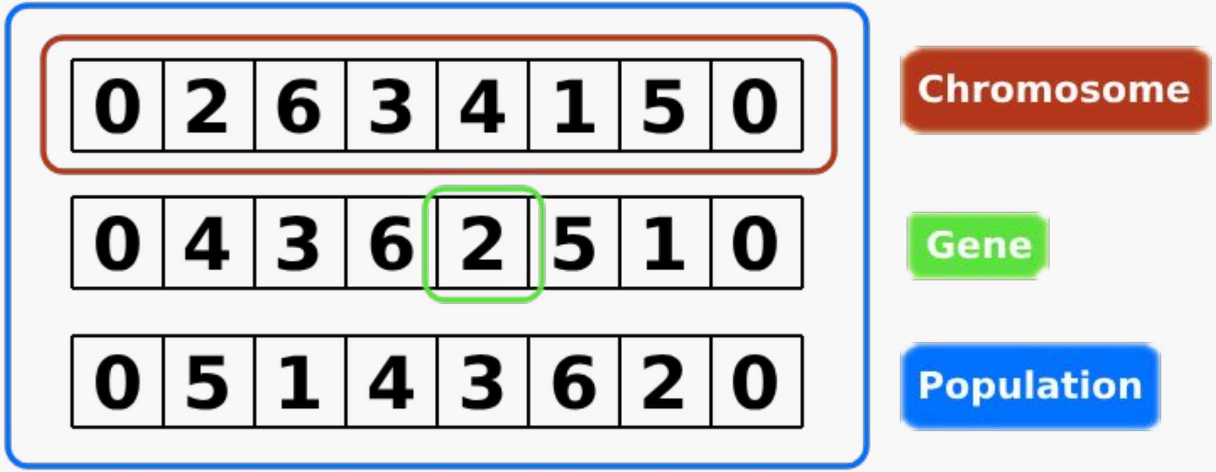
Chromosome

It's a solution to a given problem. It's an ensemble of genes.

Population

It's a subset of feasible solutions to a given problem. Basically, it's a set of chromosomes.

What does it mean...



Representation of the terminology regarding the TSP Problem

Genetic Operators

Mutation

Used to maintain diversity & avoid local minima. Does some change within a chromosome.

Crossover

Combines genetic information of two parents to generate new offsprings.

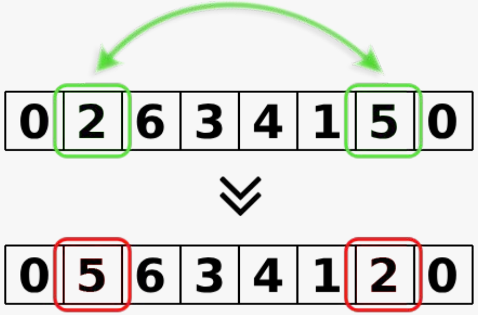
Tournament

Method of selecting an individual from the population. N elements are chosen at random -> the fittest wins.

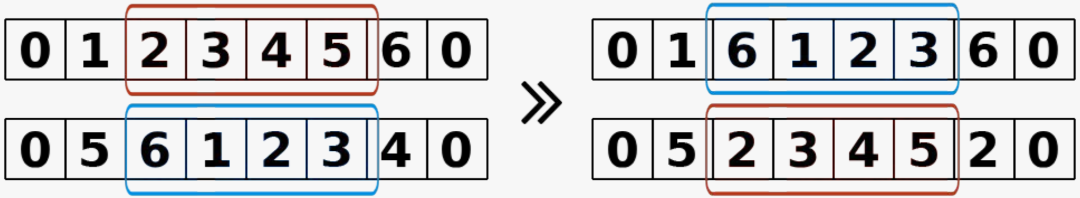
Roulette

Method of selecting an individual from the population. Each chromosome has a probability linearly correlated to its fitness level.

What does it mean...



Example of
Mutation Function



Example of
Crossover Function

Pseudo-Code

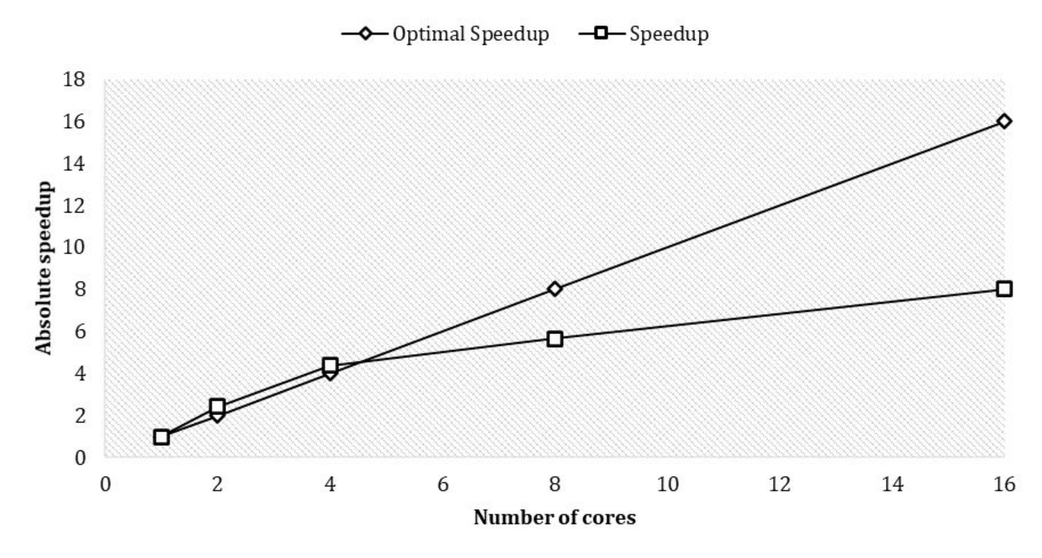
```
Begin GA
  Generate Random Population
  While NOT stop DO:
    BEGIN
        Tournament Selection
        Roulette Selection
        Generate CrossOvers
        Mutate Children
        Extend Population by Reproducing
        Remove Least Fitted
    END
  Output the best solution
END
```

Pseudo-Code for the GA

04

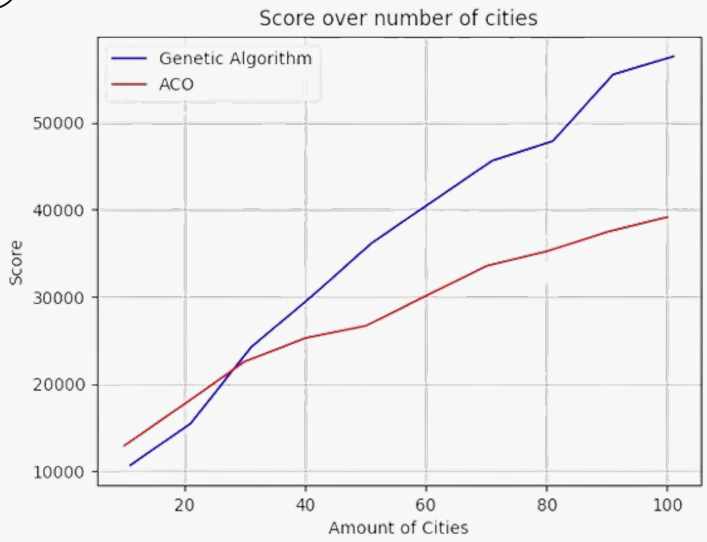
Results

ACO Serial vs Parallel



Although there is an absolute speed increase, the significant cost of node-to-node transmission makes this not so beneficial. The communication time between nodes rises with node count, which results in a drop in speedup relative to ideal speedup.

ACO vs GA


Score over number of cities
Genetic Algorithm
ACO
Score
50000
40000
30000
20000
10000
20
40
60
80
100
Amount of Cities


Execution Time over number of cities
Genetic Algorithm
ACO
Time (s)
16
14
12
10
8
6
4
2
0
20
40
60
80
100
Amount of Cities

05

Conclusions

ACO Approach Trade-Off

- Inherent parallelism & scalability;
- Ability to find near-optimal solutions;
- Adaptability to dynamic environments (to different problems & constraints);
- Balance exploration and exploitation, allowing for effective exploration of the solution space.

- Theoretical analysis is difficult;
- Sensitive to parameter settings;
- Research is experimental rather than theoretical;
- Time to convergence uncertain (but convergence is guaranteed!)

Genetic Algorithm Trade-Off

- GAs can handle a wide range of optimization problems.
- Considerably easier to code when compared to other approaches.

- Computationally expensive, especially for complex problems or large solution spaces;
- Very sensitive to parameter tuning & choice of mutation and crossover functions;
- May converge to a suboptimal solution very early on & get stuck on a local minima.

Conclusions & Remarks

- According to our results, the ACO approach performed better overall than the GA one.

- The GA achieved better results when the number of cities was lower, but was outperformed in higher inputs.

- Does it mean that the ACO approach is better than GA ?

- Perhaps for this specific problem it could be, but it all depends on various factors such as problem complexity, input size and specific requirements or constraints and even the coding approach itself.

References

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